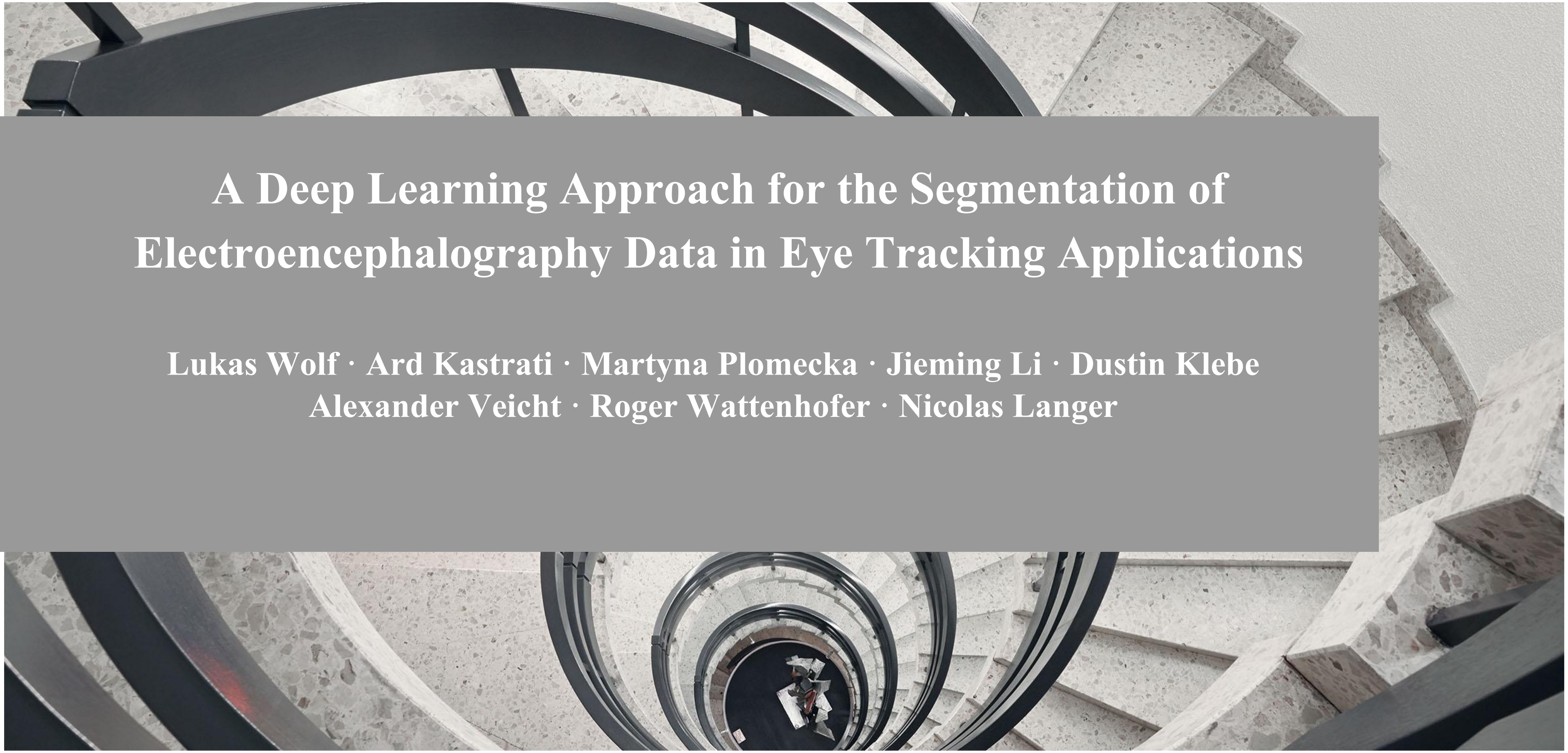

A Deep Learning Approach for the Segmentation of Electroencephalography Data in Eye Tracking Applications

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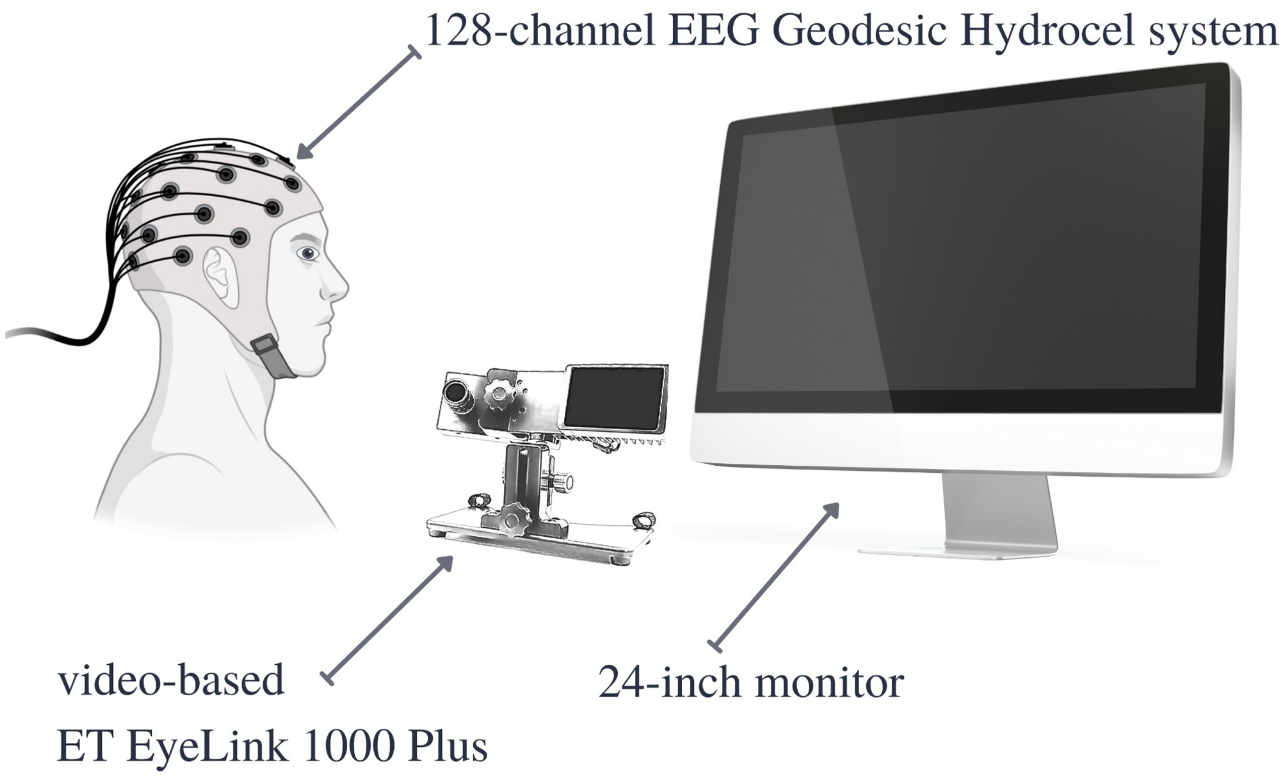
ICML International Conference On Machine Learning

Introduction and Motivation

Recording Setup



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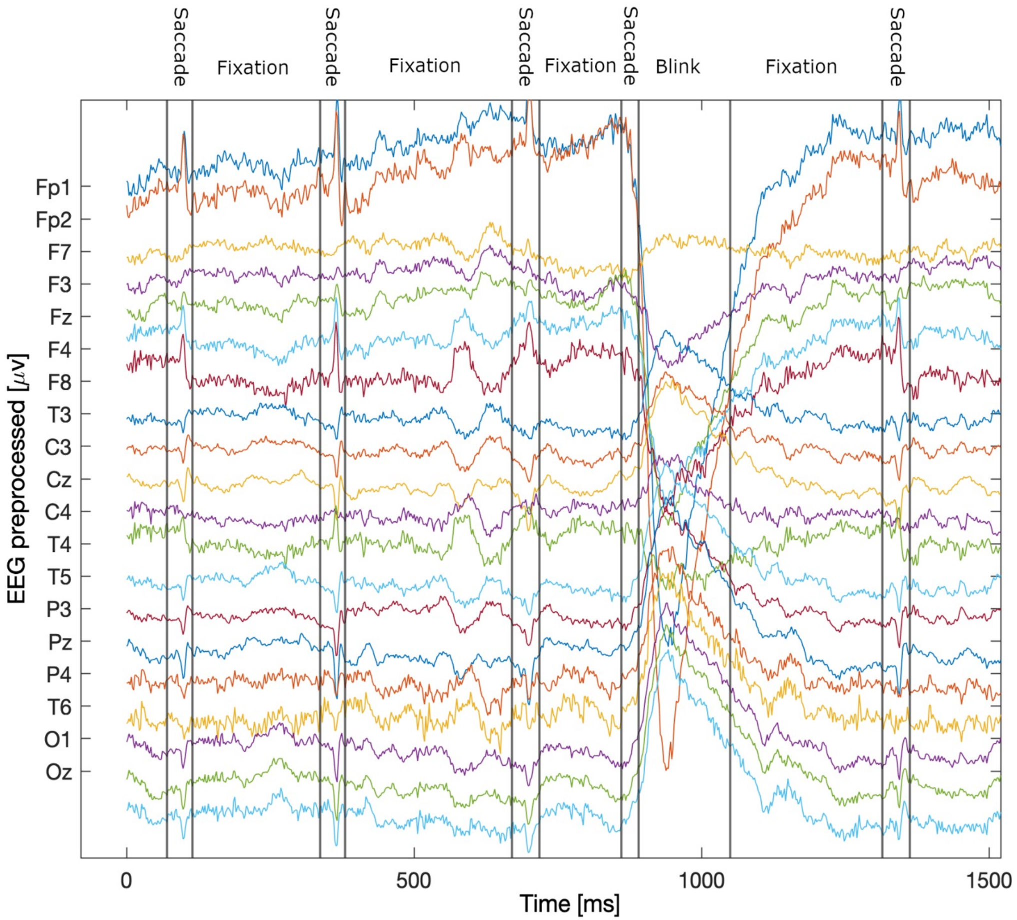
Problem Setting

- Experimental Paradigms:
  - Large Grid (Dots)
  - Visual Symbol Search
  - Natural Reading
  - Movie Watching



Related Work and Baselines

- Baseline Models:
  - State-of-the-Art CNN models (e.g. InceptionTime)
  - Recurrent models (e.g. LSTM)
  - Additional models specifically tailored for EEG data (e.g. EEGNet)
  - For comparison: standard ML techniques (e.g. random forest)

- State-of-the-Art EEG Segmentation:
  - U-Time (Perslev et al., 2019): fully convolutional neural network for physiological time series segmentation for the analysis of (EEG) sleep data, based on the U-Net architecture
  - SalientSleepNet (Jia et al., 2021): multimodal salient wave detection network for (EEG) sleep staging, based on the U^2-Net architecture

Proposed Approach: DETRtime

- We propose to predict **single, distinct** regions, in order to:
  - Counter event length imbalance
  - Simplify incorporation of global context

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- Implementation of this approach:
  DETRtime, a time series adaptation of the DETR architecture and its set matching-based Hungarian loss

DETRtime: Training

- N separate time segment predictions:
  - Time segment : (b, c) consisting of class label c and boundaries b
- Predictions are matched with ground truth via a proxy of the loss:
  - Excess predictions are matched to a "no-class" label

$$\mathbf{L}(y, \hat{y}) = \sum_{i=1}^{N} \mathbf{L}_{NLL}(\hat{c}_{\pi(i)}, c_i) + \mathbb{I}_{c_i \neq \emptyset} * \mathbf{L}_{region}(\hat{b}_{\pi(i)}, b_i)$$

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- Segmentation Output:
  - Time point assigned to the maximum confidence event over all overlapping segments

Results

Model	Large Grid				VSS			
	fix	sac	blk	avg	fix	sac	blk	avg
biLSTM	0.98	0.79	0.47	0.75	0.97	0.86	0.28	0.70
CNN-LSTM	0.99	0.84	0.52	0.78	0.97	0.88	0.24	0.70
SalientSleepNet	0.99	0.81	0.51	0.77	0.97	0.86	0.24	0.69
U-Time	0.99	0.82	0.88	0.90	0.90	0.70	0.79	0.79
DETRtime	0.99	0.87	0.90	**0.92**	0.86	0.78	0.82	**0.86**

Model	Reading				Movies			
	fix	sac	blk	avg	fix	sac	blk	avg
biLSTM	0.87	0.44	0.27	0.53	0.96	0.69	0.57	0.74
CNN-LSTM	0.87	0.44	0.34	0.55	0.96	0.70	0.56	0.70
SalientSleepNet	0.85	0.40	0.43	0.56	0.96	0.62	0.52	0.70
U-Time	0.86	0.47	0.72	0.69	0.96	0.70	0.62	**0.76**
DETRtime	0.90	0.55	0.80	**0.75**	0.96	0.69	0.63	**0.76**

Results

	Sleep-EDF-153					
Model	W	N1	N2	N3	REM	avg
SalientSleepNet	0.93	0.54	0.86	0.78	0.86	0.795
U-time	0.92	0.51	0.84	0.75	0.80	0.76
DETRtime	0.98	0.49	0.85	0.81	0.88	**0.801**

Discussion and Outlook

- Contributions:
  - Two new datasets for eye movement segmentation using EEG (Large Grid, Movies)
  - DETRtime outperforms state-of-the-art models on Sleep-EDF-153, Large Grid, Movies, VSS

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  - Gap in performance when using naturalistic settings
  - Performance for dynamic events (saccades, blinks) can still be improved

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- Insights and Opportunities:
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  - Performance for dynamic events (saccades, blinks) can still be improved
- Outlook:
  - Fine-tuning on individual participants
  - Combination of camera- and EEG-modalities

Contact

For any further questions, feel free to contact us:

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- Jie-Ming Li ljie@ethz.ch

References

- Large Grid and Visual Symbol Search Paradigms (Kastrati et al., 2021) (https://arxiv.org/abs/2111.05100)
- U-Time (Perslev et al., 2019) (https://arxiv.org/abs/1910.11162)
- SalientSleepNet (Jia et al., 2021) (https://arxiv.org/abs/2105.13864)
- U^2-Net (Qin et al., 2020) (https://arxiv.org/abs/2005.09007)

This paper on Arxiv: https://arxiv.org/abs/2206.08672